

Discovering and Reusing Knowledge in Case-bases when Cases Evolve through Time

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Case-based reasoning (CBR) is an artificial intelligence methodology for the processing of empirical knowledge. It reasons from cases, which are sets of empirical data, such as patient cases in a medical domain. Previously processed cases are stored in a case-base, or memory, and used by such a system to process new cases. The processing of a new case uses one or several memorized cases similar to the new case. It reuses these similar cases in order to propose a processing for the new case.

From a machine learning point of view, case-based reasoning is a learning method among others. More precisely, case-based reasoning systems are systems that learn through experience, and thus can follow various learning methods to achieve this goal. This poster proposes a new paradigm for enhanced case-based reasoning: **case-based discovery**. In this paradigm, **case-based reasoning** is connected with **knowledge discovery**. For example, the **MNAOMIA** case-based reasoner (and case-based discoverer) discovers knowledge through **concept learning**, and then reuses this discovered knowledge. It not only learns concepts during the course of CBR, but also reuses the concepts learnt in order to perform the task of knowledge discovery as a supplementary task to the tasks performed by its classical case-based reasoning.

The **MNAOMIA** case-based discoverer illustrates the case-based discovery paradigm in this poster. It reasons and learns from patient cases, the data of which evolve through time. So time is represented in cases, and **temporal knowledge** is discovered and reused. This system is applied to the domain of **eating disorders** in psychiatry. Its aim is to provide assistance to experts in the different cognitive tasks they perform, namely diagnosis, treatment planning, patients follow-up and clinical research. The clinical research task is the knowledge discovery task performed by **MNAOMIA**.

Knowledge discovery in **MNAOMIA** is an **incremental concept learning**. Concepts are learnt from the cases: they are called trends because they

summarize temporal data. These trends are the **organizational units** of the memory. Cases are linked to (indexed under) them. They are organized in a **generalization hierarchy**, with the most general trends at the root of the hierarchy, and the most specific ones at the bottom. The trends learning algorithm is based on the definition of **matching predicates** between representation elements El_{iC} , and El_{iT} . Since both trends and cases are expressed as conjunctions of such representation elements (either attribute-value pairs, or relation-source.node-target.node triplets), these matching predicates permit to match any of them. These predicates are :

1. **match-indep**(El_{iC} El_{iT}) matches two time-independent elements, which are elements not bound to time.
2. **match-point**(El_{iS} El_{iT}) matches two time-point elements, which are elements attached to a time-point. Each time-point t has a (min,max) range for matching.
3. **match-interval**(El_{iS} El_{iT}) matches two time-interval elements, which are elements attached to a time-interval.

Discovered knowledge reuse enables **MNAOMIA** to perform a supplementary task to the tasks performed by a CBR system. It follows the same reasoning steps as the other tasks performed. Here, the new case to process is a **query** Q . The first step is the **retrieve** step, which extracts from the memory a set of trends and cases similar to Q . The **reuse** step, is here an **interpretation**. The system proposes an argumentation around first a selection of the trends extracted, and proposes to the user to further explore the sub-trends and the cases retrieved.

Case-based discovery is a paradigm meant to improve learning in case-based reasoning. It has been evaluated in a complex real-world medical domain in the **MNAOMIA** system, where cases have a **temporal representation**, and results encourage to intensify the knowledge discovery. Future work can be to improve more the knowledge discovery, using other algorithms from this area of research, and to learn different objects, such as rules or models.